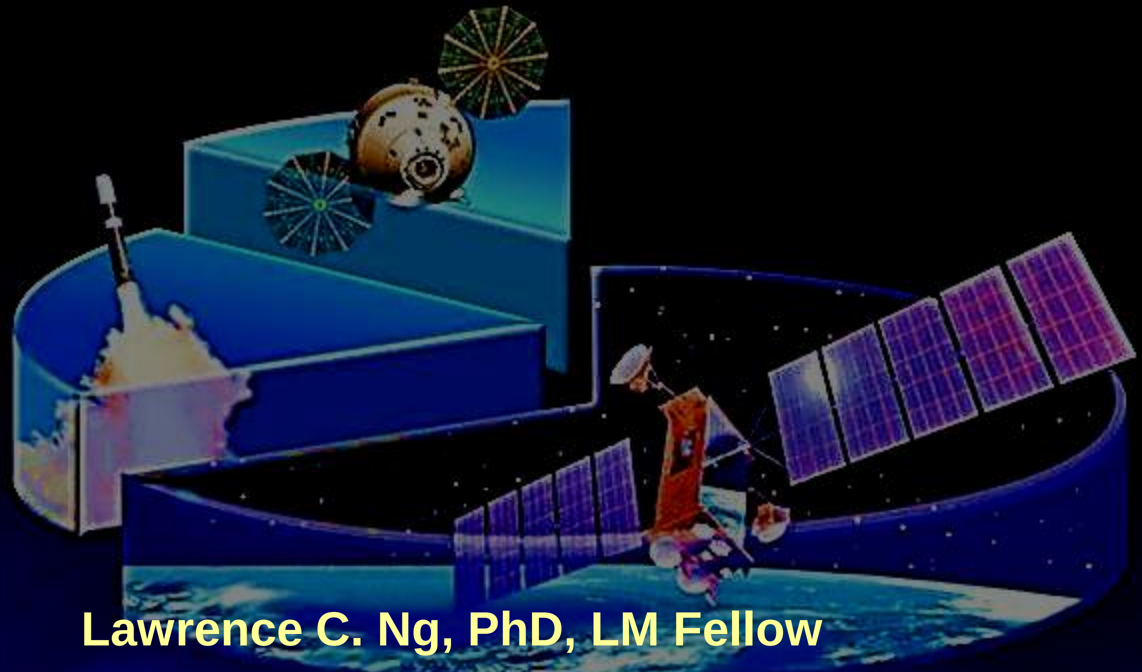
Application of Particle Filter for Target Tracking and Market Forecasting

Presented at 2013 CASIS Workshop



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Strategic and Missile Defense Systems

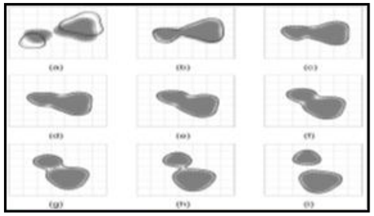
Lockheed Martin Space System Company

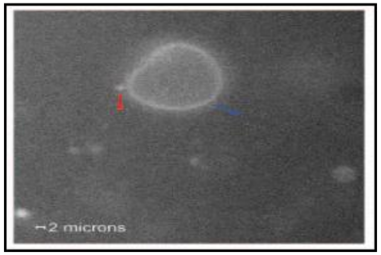
May 22, 2013

Particle Filter Technology Initiative

- SBIR/STTR funding from many Gov agencies including NIH, NSF & MDA
- Track before detect capability
- Reduce detection threshold by 4X
- Run on Massively parallel machines like GPUs

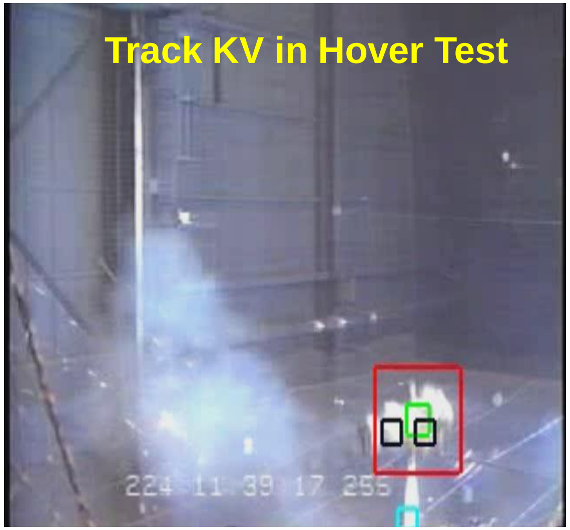
Georgia Tech Dynamic contour Particle Filter tracking of biological objects

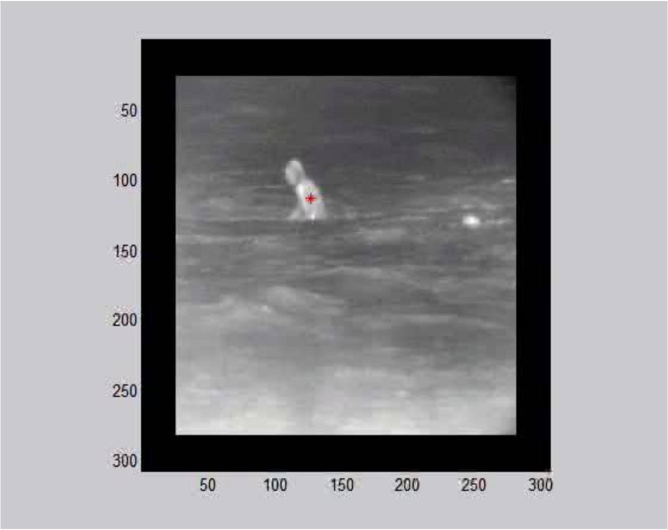




Track Cell growth

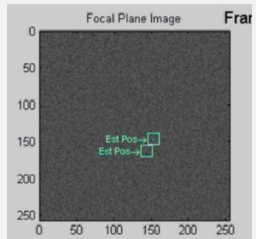
Track a female surfer





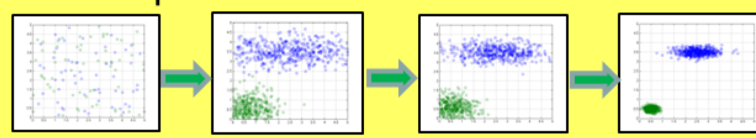
Particle Filter for Nonlinear System Parameter Estimation and Prediction

- **Small Business Partners**
  - Optimal Synthesis Inc
  - Polaris Sys Tech
  - $5M USG/LM investment



- **Commercialization**
  - Improve search engine speed & accuracy
  - Rapid message tracking for cyber defense
  - Market forecast (Optimal portfolio allocation and enhanced Black-Scholes market Option price determination)

- **Technology Highlights**
  - Search, Detect, Track & Localize multiple objects in a complex nonlinear state space
  - Maximum utilization of sensory input
  - Apps for Portfolio Investment Strategy
  - Running million particles on multiple Graphical Processor Units



LM Program Applications:

Missile Defense Applications

Satellite motion control

Space Debris tracking

General Bayesian Estimation

Aim: Construct the probability density function (pdf) of the system state vector using all available information

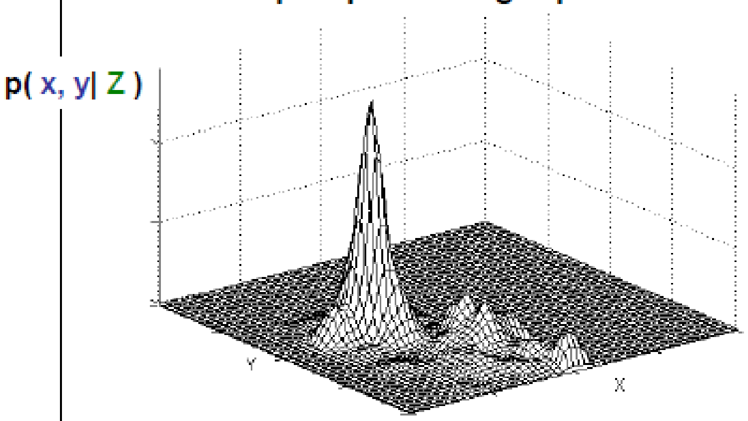
$\underline{x}$: System state vector, e.g., target position and velocity

Pdf: Provides complete statistical description of state of knowledge about system uncertainties

$p(\ \underline{x}\ |\ Z\ )$

$\underline{Z}$: Set of all available measurements, classifications, etc.

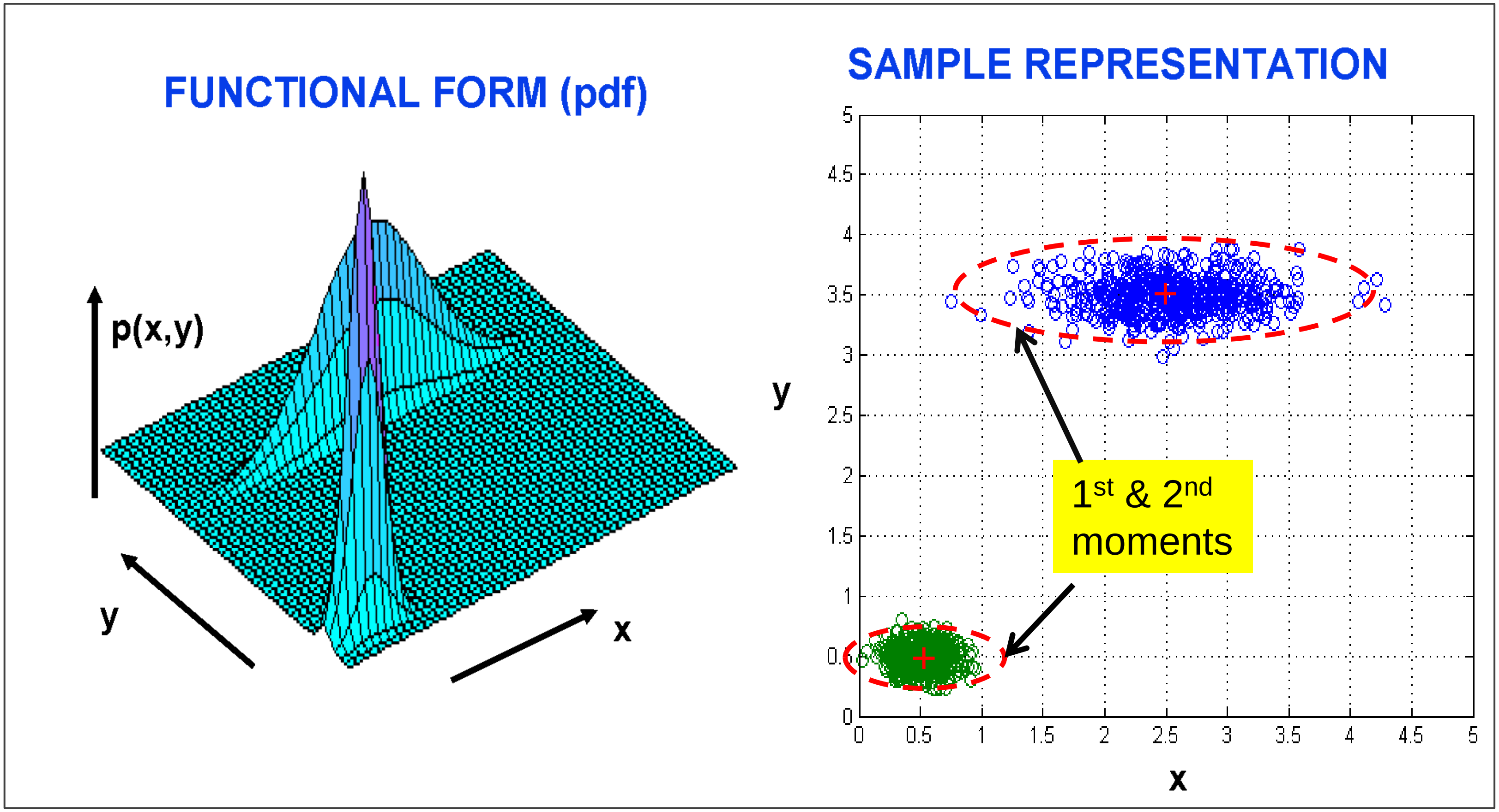
For example: pdf of target position



For nonlinear, non-Gaussian systems, knowledge of the pdf is the key to optimal estimation, decision, and control.

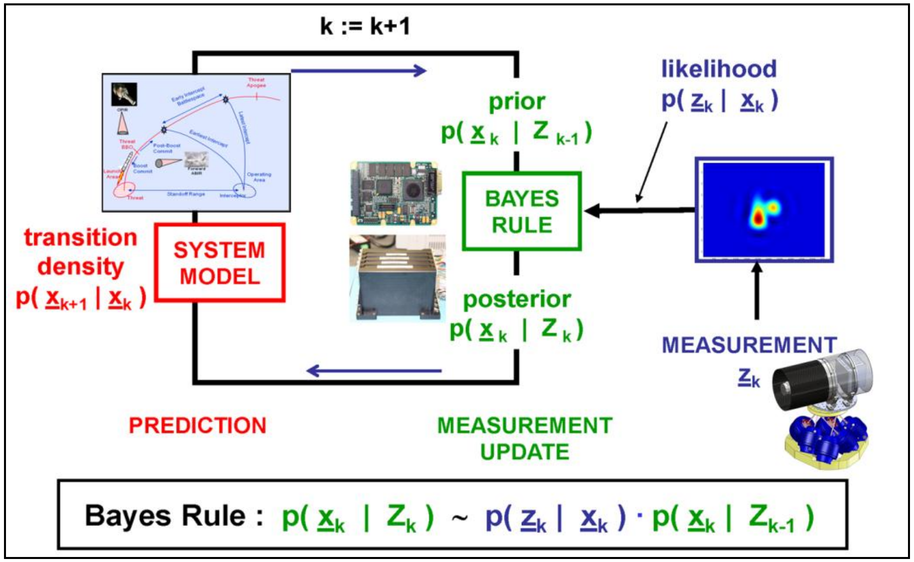
Principle of Particle Filter

- **Estimate statistical distribution of target uncertainty by propagating & adjusting a large set of random samples (particles)**



Bayesian (Monte-Carlo) Recursive Estimation

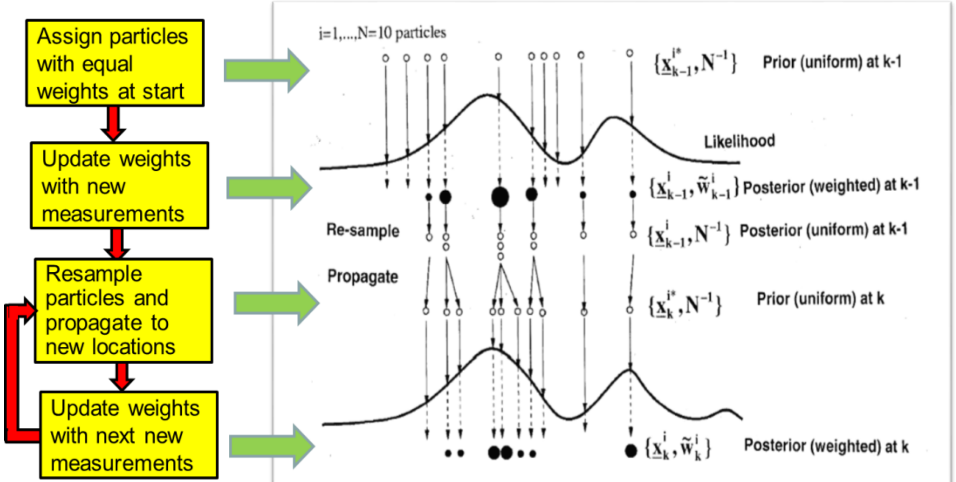
	Criteria	KF	PF
1	**Gaussian statistics**	Yes	Yes
2	**Non Gaussiaan Statistics**	No (Mean & Cov only)	Yes (pdf)
3	**Linear Dyanmics**	Yes	Yes
4	**Nonlinear Dynamics**	EKF (Linear expansion)	Particle Propagation
5	**Cold Start**	No, initialized near true state	Yes, shot gun with particles
6	**Convergence time**	Trade filter gains with noise	Fast
7	**Computation**	Simple but requires matrix inversion	Complexity increase with number of particles
8	**Track before detect**	No	Yes
9	**Multiple Targets**	Need external data association logic	Captured in the measurement model



Results from tacking a target across an image plane

KF: Increases gains reduces response time and has higher noise

PF: Consistent fast convergence and low noise

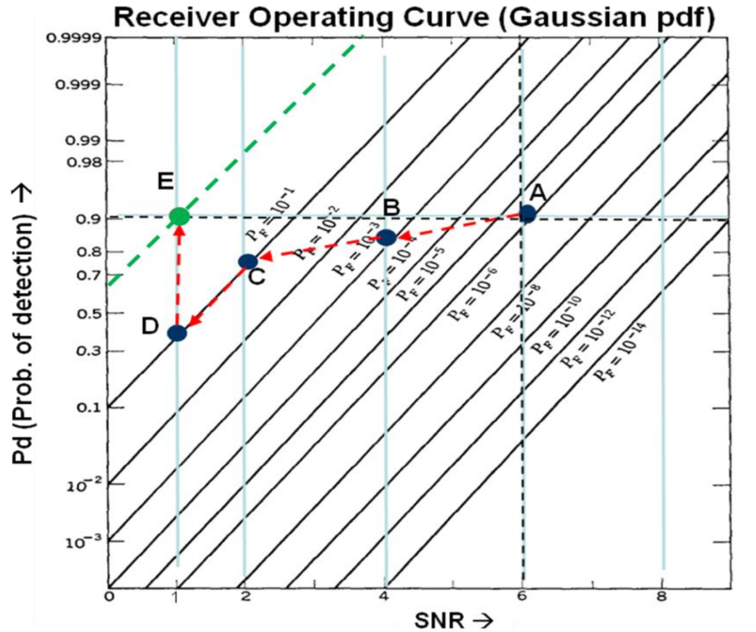


Taken from: R. van der Merwe, A. Doucet, N. de Freitas, and E. Wan, "The Unscented Particle Filter," Tech. Rept. CUED/F-INFENG/TR 380, Cambridge Univ. Engr. Dept., 2000.

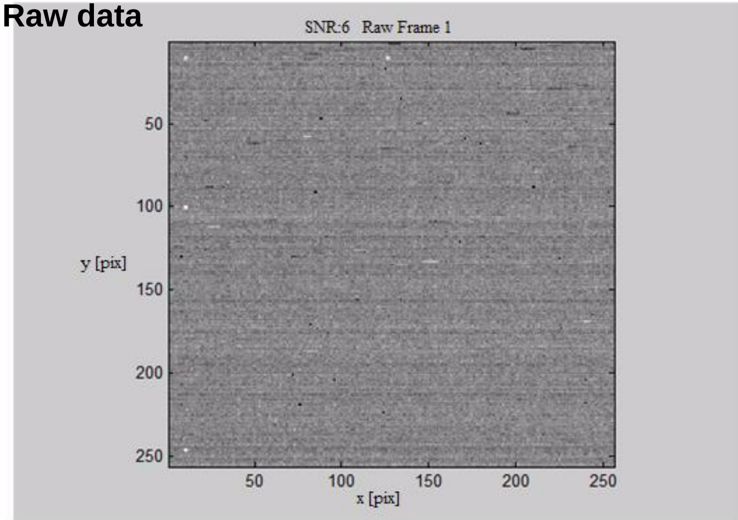
Multiple Target Tracks : 4 Targets at SNR = 6

Particle Filter Advantages:
- > 4X reduction in detection threshold
- > 2X increase in detection range

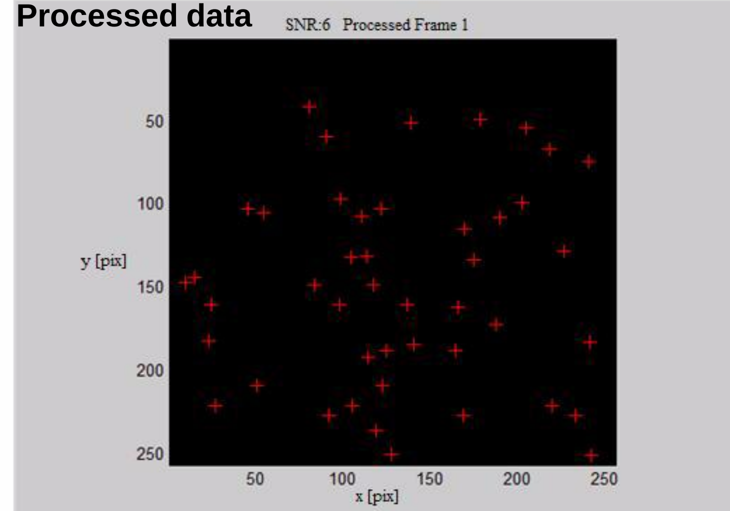
SNR	Pd (Prob. of Detection)	Pfa (Prob. of False Alarm)
6	0.9	10^-6
4	0.8	10^-3
2	0.7	10^-1
1	0.3	10^-1



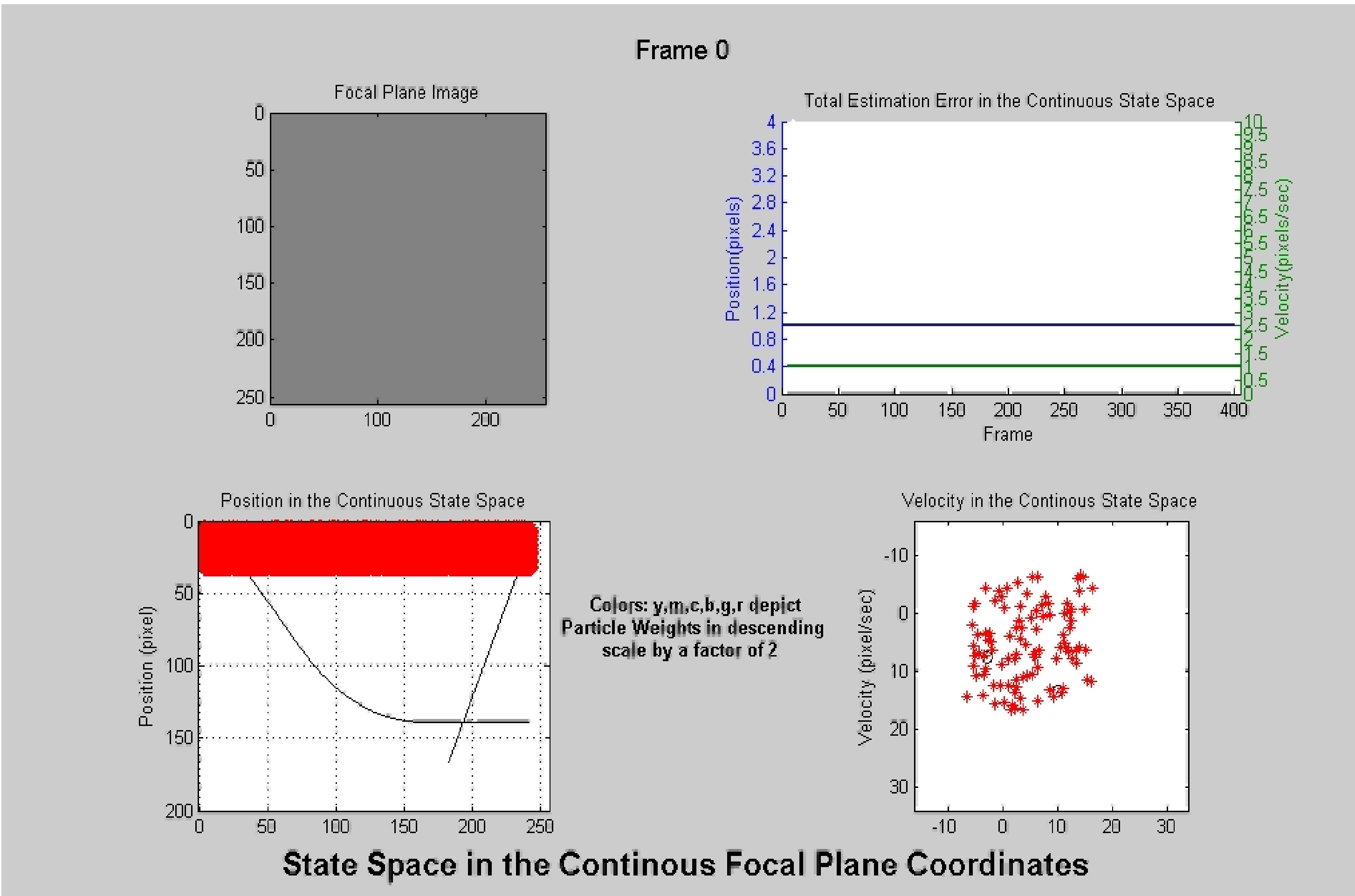
Raw data

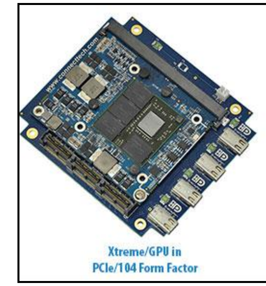


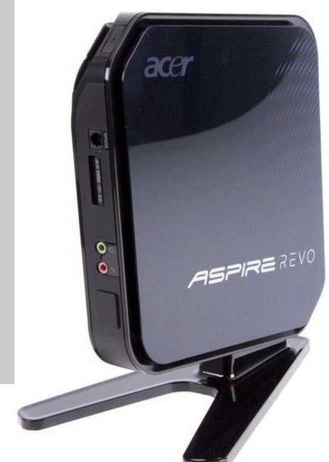
Processed data



Tracking Two Targets at SNR =1 and 6

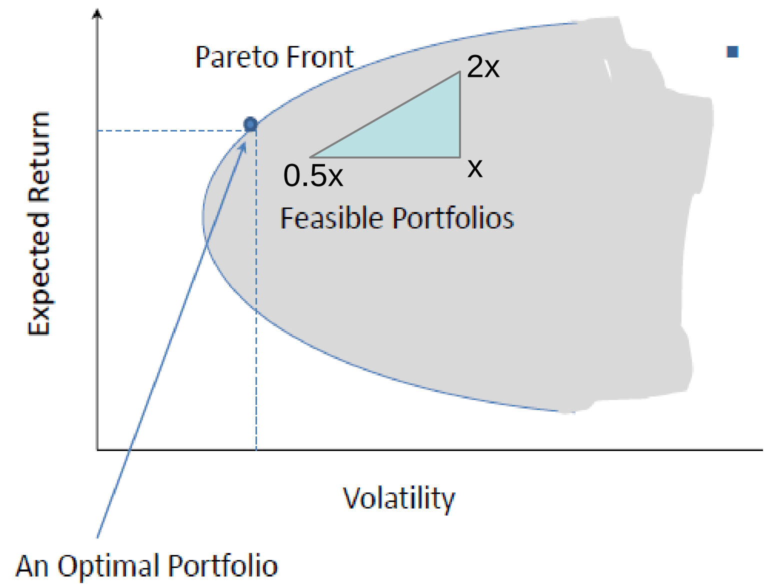






Modern Portfolio Theory (Harry Markowitz 1950)

- **Price movements are unpredictable**
- **The changes in market prices of securities can be described by the Brownian motion (Random walk)**
- **Price changes (or return) are normally distributed**
- **The decisions available to an investor are the proportions of available investments to match their risk-reward profile**



(1) $$p_{k+1}^{i} - p_{k}^{i} = N\left(\mu^{i}, \sigma^{i}\right)$$ Price of of security *i* at time k

(2) $$R^{i} = p_{k}^{i} - p_{0}^{i}$$ Return on Investment (ROI)

(3) $$R = \sum_{i=1}^{N} X^{i} R^{i}$$ Portfolio ROI; linear in X^i; X^i are fractional allocation

(4) $$V = \sum_{i=1}^{N} \sum_{j=1}^{N} \rho_{ij} X^{i} X^{j}$$ Portfolio Risk (quadratic)

Find max E{R} , from pdf

$$P(R \mid X, V, Z)$$

= A Posterior pdf of ROI R conditioned on portfolio X, risk V, and market data Z

Preliminary Results: 2X return for a given risk; Same return at 50% risk